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ABSTRACT

An important but too infrequently considered methodology that can be used in research involves testing for moderator and mediator variable effects. This paper distinguishes between the properties of moderator and mediator variables. The moderator functions to partition a main independent variable into subgroups that establish its domains of maximal effectiveness in regard to a given dependent variable. The mediator functions to represent the generative mechanism through which the main independent variable is able to influence the dependent variable of interest. Careful elaboration regarding the many ways in which moderators and mediators differ can make researchers and theorists aware of the importance of not using the terms interchangeably. A review of the analytic methods used for detecting mediating and moderator effects provides conceptual and statistical considerations for evaluating these effects. (Contains 31 references.) (Author/SLD)

A Review of Analytic Methods for Detecting Mediating and Moderator Effects

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Abstract

An important but too infrequently considered methodology that can be employed in research involves the testing for moderator and mediator variable effects. The purpose of this paper is to attempt to distinguish between the properties of moderator and mediator variables. Careful elaboration regarding the many ways in which moderators and mediators differ can make researchers and theorists aware of the importance of not using the terms interchangeably. A review of the analytic methods used for detecting mediating and moderator effects will provide conceptual and statistical considerations for evaluating these effects.

An important but too infrequently considered methodology that can be employed in research, especially research focusing on Pearson *r* (Walsh, 1996) or the multiple *R* (cf. Thompson, 1992), involves testing for moderator or mediator variable effects. The purpose of this paper is to distinguish between the properties of moderator and mediator variables and to review the analytic methods for detecting its effects.

Mediator and Moderator Distinction

Baron and Kenny (1986) differentiate between the two often-confused functions of third variables. The moderator functions to partition a main independent variable into subgroups that establish its domains of maximal effectiveness in regard to a given dependent variable. The mediator functions to represent the generative mechanism through which the main independent variable is able to influence the dependent variable of interest. It is not all uncommon for psychological researchers to use the terms interchangeably, despite these two functions of third variables having long been recognized in the social sciences (Baron & Kenny, 1986). Failure to appreciate the moderator-mediator distinction inhibits the researcher in exploring the nature of causal mechanisms and integrating different theoretical positions.

Rozeboom (1956) provided a number of clear lines of delineation between the terms mediator and moderator. In particular, the moderator model is represented by a single, nonadditive, linear function in which it is desirable to have minimal covariation between the moderator and both the independent and dependent variables (Abrahams & Alf, 1972). In comparison, mediation models must be represented by at least two additive, linear functions in which it is desirable to have high degrees of covariation between the mediator and both the antecedent and consequence (James & Brett, 1984). It is purposeful in the use of the terms *independent and dependent* in moderator models, and *antecedent* and *consequence* in mediator models. It indicates that moderation carries with it no connotation of causality, while mediation implies at the minimum a causal order, and often additional causal implications are required to explain how mediation occurred (cf. Stolzenberg, 1979).

In general terms, a moderator is a qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable (Baron & Kenny, 1986). Specifically, within a correlational analysis framework, a moderator is a third variable that affects the correlation between two other variables (cf. Walsh, 1994). A moderator effect may also be said to occur where the direction of the bivariate correlation changes across variations in the "third" variable.

From within the analysis of variance framework (ANOVA), a basic moderator effect can be represented as an interaction between a main independent variable and a factor that specifies the appropriate conditions for its operation. A model provided by Baron and Kenny (1986), shown in Figure 1, has three causal paths that feed into the outcome variable: the impact of the predictor (Path a), the impact of a moderator (Path b), and the interaction or product of these two (Path c). The moderator hypothesis is supported if the interaction (Path c) is statistically significant. There may also be separate statistically significant main effects for the predictor and the moderator (Paths a and b), but these are not directly relevant conceptually to testing the moderator hypothesis (Baron & Kenny, 1986).

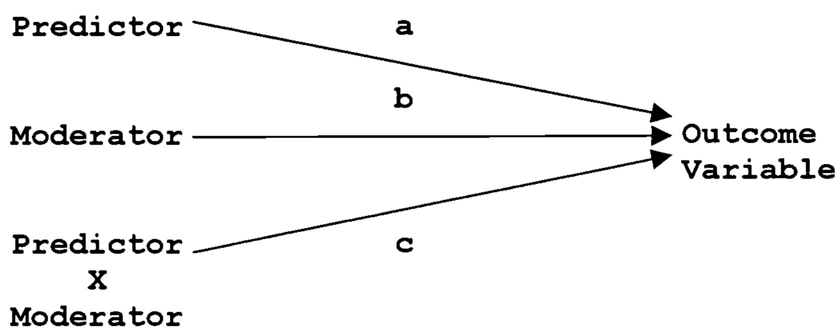

Figure 1. Moderator model

To provide a clearly interpretable interaction term, it is desirable that the moderator variable be uncorrelated with both the predictor and the dependent variable. Unlike a mediator-predictor relation, moderators and predictors are at the same level in regard to their role as causal variables antecedent to certain criterion effects. In other words, moderator variables always function as independent variables, whereas mediating events shift roles from effects to causes, depending on the focus of the analysis.

The central theory behind mediating variables is that various cognitive processes within an individual mediate the effects of stimuli on behavior. A particular variable may be said to function as a mediator to the extent that the variable accounts for the relation between the predictor and the criterion. In general, mediators explain how external physical events take on internal psychological significance. In comparison, moderator variables specify *when* certain effects will hold, whereas mediators speak to *how* or *why* such effects occur (Baron & Kenny, 1986). For example, to clarify the meaning of mediation, a path diagram in Figure 2 depicts a causal chain. The basic causal chain assumes a three-variable system such that there are two causal paths feeding into the outcome variable: the direct causal impact of the independent variable (Path c), and a path from the independent variable to the mediator (Path a) with the subsequent impact of the mediator (Path b).

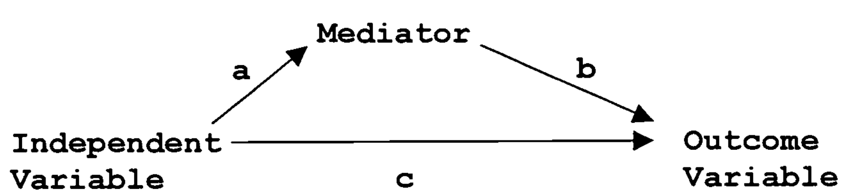

Figure 2. Mediational model.

Specifically, a variable functions as a mediator when the variable meets the three following conditions. First, variations in the levels of the independent variable significantly account for variations in the presumed mediator (i.e., Path a). Second, variations in the mediator significantly account for variations in the dependent variable (i.e., Path b). And third, when Paths a and b are experimentally controlled, a previous relation between the independent and dependent variables is no longer statistically significant. When Path c is non-existent statistically, the strongest demonstration of mediation is considered to occur. As different areas of psychology treat a wide range of phenomena that have multiple causes, a more realistic perspective may be to seek mediators that significantly decrease the independent variables influence on the outcome variable rather than eliminating the relation altogether.

However, things are not necessarily as straightforward as the previous distinctions suggest, one reason being that mediating variables may involve or be influenced by a moderator creating a situation termed "moderated mediation." In these hybrid situations, moderation may be functionally involved in the first-stage of a mediation relation (James & Brett, 1984). In some circumstances, it may be impossible to classify a particular variable as either a mediator or a moderator because the variable may interact as both in a causal model or system (Simon, 1977).

Detecting Mediation Effects

At a simplified theoretical level, a "complete mediation model" has the form $x \rightarrow m \rightarrow y$, where x is the antecedent, m is the mediator, and y is the consequence.

With this complete mediational model the antecedent x is expected to affect the consequence y only indirectly through transmission of influence by the mediator m. This indirect transmission of influence from x to y via m signifies that all of the effect of x on y is transmitted through m (James & Brett, 1984). If these predictions are empirically confirmed, then one may infer that the complete mediation model has been supported and therefore is useful for attempting to explain how x is related to y through the intervening mediator m (James, Mulaik, & Brett, 1982).

A complete mediation model can be tested using analytic procedures typically associated with exploratory correlational analysis, such as hierarchical regression and/or partial correlation (James & Brett, 1984). Methods such as hierarchical regression and partial correlation are typically used as confirmatory tests (Cohen & Cohen, 1983). However, these methods are limited in regard to both types of causal models for which they are applicable and the information they provide (Griffin, 1977).

Hierarchical Ordinary Least Squares

The relation that mediating variables possess may be tested empirically by applying hierarchical ordinary least squares procedures to operationalize functional equations (Stolzenberg, 1979). Mediation functions may involve nonrecursive relations, such as x $\rightarrow$ m $\leftrightarrow$ y, where there exists a reciprocal causation between m and y.

Another design possibility involves cyclical recursive feedback loops, such as x $\rightarrow$ m $\rightarrow$ y $\rightarrow$ x, with a specified time interval, from y back to x. Cyclical recursive designs require an empirical test with time-series analysis, in which each variable is measured at a distinct time period that reflects the causal interval required for cause-effect relations to stabilize (James et al., 1982).

There are many types of causal mediation relations and models. Yet, all have the common attribute that the mediator transmits influence from an antecedent to a consequence. The transmission need not involve all of the influence from an antecedent on the consequence, nor need the mediation relation be additive, linear, or recursive (James & Brett, 1984).

The purpose of designing a confirmatory test of causal mediation is to ascertain whether the model is useful for explaining how particular variables occurred and are related (cf. James et al., 1982). Confirmatory tests should only be conducted on causal models for which the confirmatory analyses have been reasonably satisfied.

A specification error is a general term used by James and Brett (1984) to indicate that one or more conditions for confirmatory analysis have not been reasonably satisfied. Specification errors (i.e., models with incorrect variables or containing incorrect paths or relationships) are symptomatic of an incomplete transition from exploratory analysis to confirmatory analysis. Typically, the errors become apparent only after knowledge accumulates regarding all of the conditions necessary for a meaningful confirmatory analysis. In other words, we usually cannot be sure whether a model we are testing is correctly specified, and exactly where misspecification may be occurring.

Quite often, psychological research develops causal mediation models with obvious misspecifications (i.e., unmeasured variables, unanalyzed reciprocal causation) which have been subjected to goodness-of-fit tests using hierarchical ordinary least squares (OLS) and/or partial correlation analyses (James & Brett, 1984). These tests should be regarded as exploratory tests of correlational mediation hypotheses, but unfortunately are too often interpreted as confirmatory tests of causal hypotheses and used to make causal inferences of a mediational path.

It would be more practical if investigators devote more attention to all of the conditions for analysis before conducting confirmatory tests on causal models and using the results of these tests to support causal inferences. On the other hand, Griffin (1977) supports the use of confirmatory analytic techniques such as path analysis and structural equation analysis if all sources of misspecification are considered, and no major admissions of new variables are considered likely. These particular techniques have the ability to perform several functions; to test causal hypotheses that cannot be addressed by classical correlational techniques, can estimate causal parameters, and are a basis for estimating "indirect effects."

Regression Models

Fiske, Kenny, and Taylor (1982) extensively discussed the testing of the mediational hypothesis, and reported that an ANOVA procedure provides a limited test of this model. Judd and Kenny (1981b), recommend a series of regression models to be estimated. To test for mediation, one should estimate the three following regression equations: first, regressing the mediator on the independent variable; second, regressing the dependent variable on the independent variable; and third, regressing the dependent variable on both the independent variable and on the mediator. In addition to regression equations, it is suggested that separate coefficients for each equation should be estimated and tested (Baron & Kenny, 1986). These three regression equations provide the tests of the linkages of the mediational model. There are several conditions that must be met to establish mediation: first, the independent variable must affect the mediator in the first equation; second, the independent variable must be shown to affect the dependent variable in the second equation; and third, the mediator must affect the dependent variable in the third equation. Support of the mediational linkage occurs if the results all maintain their predicted direction, and the effect of the independent variable on the dependent variable must be less in the direct path than in the path through the mediating variable. Perfect mediation holds if the independent variable has no effect when the mediator is controlled (Baron & Kenny, 1986).

Multiple Regression

Because the independent variable is assumed to cause the mediator, these two variables should be correlated. The presence of such a correlation results in multicollinearity when the effects of independent variable and mediator on the dependent variable are estimated. This results in reduced power in the test of the regression coefficients in the third equation. It is then critical that the investigator examine not only the statistical significance of the coefficients but also their effect size (Thompson, 1989). The use of multiple regression to estimate a mediational model requires the assumptions that there be virtually no measurement error in the mediator and that the dependent variable not cause the mediator (Baron & Kenny, 1986).

Because the mediator is often an internal, psychological variable, mediation is likely to be measured with some measurement error. The presence of measurement error in the mediator tends to produce an underestimate of the effect of the mediator and an overestimate of the effect of the independent variable on the dependent variable when all coefficients are positive (Judd & Kenny, 1981a). Obviously this is not a desirable outcome, because successful mediators may then be overlooked.

Generally the effect of measurement error is to constrict the size of measures of association, the resulting estimate being closer to zero than it would be if there were no measurement error (Judd & Kenny, 1981a). The consequence not having control of measurement error in the mediator will effect accurate measurement of the independent variable on the dependent variable. The common approach to unreliability is to have multiple measures or indicators of the construct (Baron & Kenny, 1984). Such an approach requires two or more indicators of each construct. One can use the multiple indicator approach and estimate mediation paths by latent-variable structural modeling methods (Thompson, in press).

Structural Equational Modeling

Structural modeling, sometimes called causal modeling, examines the patterns of correlation among variables to determine their consistency with an a priori causal model (Bentler, 1980). Although structural modeling is at least somewhat useful for inferring causality with correlational data, experimental control adds even more power to the technique (Fiske, Kenny, & Taylor, 1982). Structural modeling has three major advantages over traditional methods. First, it forces the researcher to be explicit about assumptions. One cannot easily hide implausible or contradictory assumptions. Second, the researcher has great flexibility in the rival models that can be tested. For instance, the researcher can allow for causal effects between theoretical constructs, as opposed to simply equating a measured variable with the underlying construct. Third, one can directly test some of the model's assumptions, especially reliability assumptions, many of which often go untested with other techniques.

Similar to factor analysis, structural modeling assumes that the underlying factor "causes" answers to specific items on that dimension. Thus, the model includes a test of the coefficients of the multiple indicators on the attribution factor. The factor analysis, then, provides a better representation of the underlying dependent variable. Hence, the factor analysis yields a better estimate of the paths between other variables and the causality dependent measure (Kenny, 1979). Contrary to conventional wisdom, path analysis is even more valuable in an experimental context that with non-experimental data. In particular, path analysis can neatly separate these mediational networks than can standard ANOVA methods (Fiske, Kenny, & Taylor, 1982). Whereas an ANOVA can confound the direct causal effect of a manipulation with its indirect effect through the mediator, path analysis can be combined with factor analysis in structural modeling. Such a procedure recognizes that a single dependent measure only imperfectly taps the underlying theoretical construct.

Detecting Moderating Effects

Zedeck (1971) defined a general moderator variable as a qualitative or quantitative variable that improves the usefulness of a predictor by isolating subgroups of individuals for whom a predictor or set of regression weights are especially appropriate. As previously discussed, a moderator variable is assumed to affect the nature and/or degree of association between a criterion variable and a given correlate or set of correlates (Zedeck, 1971). As the value of the moderator changes there are systematic changes in the relationship between the other two variables (Stone-Romero & Anderson, 1994).

Subgrouping versus Moderated Multiple Regression

A number of statistical methods have been used to detect moderator variables and to describe their effects: the subgrouping strategy (Arnold, 1982; Zedeck, 1971) and the moderated regression strategy (cf. Stone, 1988; Zedeck, 1971). As explained by Gall, Borg and Gall (1996), moderator analysis

> involves identifying a subgroup for whom the correlation between a criterion and a predictor variable is significantly greater than the correlation for the total sample from which the subgroup was formed. (p. 425)

The subgrouping strategy involves testing the equality of two or more subgroup-based correlation coefficients (SCC). It entails the formation of K subgroups on the basis of scores on a moderator variable, computing correlation coefficients between two other variables on a within-subgroup basis, and testing the resulting K coefficients for equality (Stone-Romero & Anderson, 1994). On the other hand, the moderated multiple regression (MMR) strategy tests for a statistically significant interaction between a moderator variable and another variable in predicting values of a third variable by using ordinary least squares regression (Stone, 1988; Zedeck, 1971).

Both the MMR and SCC approaches can be used to show that the strength or degree of relationship between two variables varies as a function of the moderator third variable. A distinction between the analytic approaches can be made, as in the case of the SCC approach differences in the strength or degree of relationship are reflected by differences in the magnitudes of zero-order correlation coefficients across K subgroups. In the case of the MMR approach, differences in the strength or degree of a relationship are indexed by differences in the slopes of the regression coefficients at different levels of the moderator variable. When comparing the two strategies, Stone-Romero and Anderson (1994) reported that across all effect sizes, sample sizes, and reliabilities of predictor variable conditions, the MMR strategy was far superior to the SCC strategy in the detection of moderating effects. However, as Alexander and DeShon (1994) demonstrated, that conclusion does not apply to instances in which the moderator is a natural dichotomy (e.g., gender).

When the interaction effects are suspected and the focal variables are continuous, it has been suggested that hierarchical multiple regression be used to evaluate these moderator hypotheses (Dunlap & Kemery, 1987). Morris, Sherman, and Mansfield (1986) pointed out that the search for empirical evidence of moderator influences has been disappointing. They suggested using an alternative form of the ordinary least squares-moderated multiple regression procedure with the use of a biased estimation procedure, known as principle component regression. Despite reporting supportive results using the remedial procedure, Cronbach (1987) proclaimed the unconventional regression analysis reported by Morris, Sherman, and Mansfield (1986) to be unacceptable. Cohen (1978) had stated that moderated multiple regression (MMR) provides an unambiguous test of moderator effects. A reanalysis of Morris et al.'s (1986) data by Dunlap and Kemery (1987) demonstrated that the original OLS-MMR procedure is clearly appropriate when researchers are interested in moderator variable effects.

Fixed versus Random Effects Models

With the growing popularity of meta-analysis as a method for combining information across studies, increasing attention is being directed toward the statistical models that analysts are using and the assumptions that underlie these models (Overton, 1998). The two general classes of models commonly used are the fixed-effect (FE) and the random-effect (RE)(see Frederick, 1999). The definition of a FE model in meta-analysis terminology is a model that does not account for between-study differences, except possibly for those differences associated with a specified moderator variable (Erez, Bloom, Wells, 1996). The RE model acknowledges true between-study differences and is typically described as a two-stage or hierarchical model.

These two models imply very different statistical and sampling assumptions (Erez et al., 1996). Overton (1998) compared the two models and reported that the FE model provides a reasonably accurate assessment of moderator variable effects. By relying on unweighted estimates, the FE model guards against the potentially biasing effect of relationships that differ across levels of the moderator variable. However, not weighting fails to minimize sampling error variance, and as a result the FE model is less than optimal in its power to detect true moderator effects.

It was also reported that the RE (or mixed) models were shown to be very accurate for detecting moderating effects when between-study differences were random (Overton, 1998). In general, the RE (mixed) models may somewhat overestimate the actual variability and yield confidence intervals that are too large. But a conservative approach with the RE model seems appropriate for research situations that are ill-defined or when a large disparity exists between sample and population domains. On the other hand, the FE models appear best suited for relatively well-developed research areas or situations where narrow conclusions are acceptable (i.e., when the contextual conditions are sufficiently defined and the sample domain closely matches the population domain).

Summary

In summary, an important but too infrequently considered methodology that can be employed in research that involves testing for moderator or mediator variable effects. The purpose of this paper is to distinguish between the properties of moderator and mediator variables and to review the analytic methods for detecting its effects.

Where moderation carries with it no connotation of causality, mediation implies at the minimum a causal order, and often additional causal implications are required to explain how mediation occurred. In general terms, a moderator is a qualitative or quantitative variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable. A mediator is a variable that accounts for the relation between the predictor and the criterion. Mediators attempt to explain how external physical events take on internal psychological significance.

The relation that mediating variables possess may be tested empirically by applying hierarchical ordinary least squares procedures to operationalize functional equations. When testing of the mediational hypothesis an ANOVA procedure provides a limited test of this model, where a series of regression models should be estimated. It is then critical that the investigator examines not only the statistical significance of the coefficients but also their effect size. Because of measurement error in the mediation, one can use the multiple indicator approach and estimate mediation paths by latent-variable structural modeling methods.

A number of statistical methods have been used to detect moderator variables and to describe their effects: the subgrouping strategy and the moderated regression strategy. When comparing the two strategies across all effect sizes, sample sizes, and reliabilities of predictor variable conditions, the MMR strategy was shown to be far superior to the SCC strategy in the detection of moderating effects.

The two general classes of models commonly used in meta-analysis are the fixed-effect (FE) and the random-effect (RE) models. The FE model provides a reasonably accurate assessment of moderator variable effects, but is less than optimal in its power to detect true moderator effects. Whereas, it was also reported that the RE (or mixed) models were shown to be very accurate for detecting moderating effects when between-study differences were random.

It is not all-uncommon for psychological researchers to use the terms moderator and mediator interchangeably and a failure to appreciate the moderator-mediator distinction inhibits the researcher in exploring the nature of causal mechanisms and integrating different theoretical positions. By making the distinction, investigators will be able to add to the depth and breadth of research and theory to increase the understanding of third variables that can influence dependent outcome variables.

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